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Students' Psychological Well-Being in The Context of Generative Artificial Intelligence: Technostress, Cognitive Offloading and Emotional Dependence

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Abstract: Within less than three years, generative artificial intelligence (GenAI) has reshaped not only learning practices in higher education but also the psychological landscape of student life. This paper presents a theoretical-analytical review of empirical research published between 2020 and 2026 on the impact of GenAI on students' psychological well-being. Drawing on 32 sources indexed in Scopus and Web of Science, the study substantiates a three-loop model of psychological risk in GenAI-mediated learning: a technostress loop (techno-overload, techno-invasion, techno-uncertainty), a cognitive loop (cognitive offloading, "cognitive debt", declining critical thinking) and an affective-relational loop (emotional dependence, loneliness, problematic use). The relationship between the intensity of GenAI use and well-being is shown to be non-linear and mediated by self-regulated learning, AI literacy and academic self-efficacy. A four-module psycho-pedagogical support programme, AI-WELL, designed to build students' cognitive resilience, is proposed. The findings may inform digital-hygiene policy in Central Asian universities.

Keywords: Psychological well-being, generative artificial intelligence, technostress, cognitive offloading, emotional dependence, AI literacy, self-regulated learning, students, higher education.

Introduction: In less than three years, generative artificial intelligence has moved from a technological novelty to an everyday instrument of academic work. According to UNESCO, no educational technology of the twenty-first century has spread so rapidly while remaining so poorly supported by regulatory and ethical frameworks [1]. Studies of the student experience reveal an ambivalent picture: learners value personalised support, accessible feedback and the lowering of language barriers, yet they simultaneously express concern about the accuracy of information, academic integrity and their own intellectual autonomy [2; 3].

Psychological science approached this phenomenon with some delay. The first wave of publications focused on didactic outcomes — achievement, engagement and the quality of written work. A systematic review by M. Jukiewicz, however, demonstrates that the impact of GenAI on learner well-being constitutes a research object in its own right, not reducible to academic performance [4]: what is at stake is a reconfiguration of coping strategies for academic stress, of patterns of cognitive effort allocation and of the sources of emotional support.

For the higher education system of Uzbekistan the problem is pressing for two reasons. First, the pace of university digitalisation outstrips the pace at which teaching staff and psychological services are being prepared to address the new risks. Second, a substantial proportion of students adopt GenAI tools informally, outside any methodological guidance, which increases the likelihood of dysfunctional usage patterns.

The aim of this paper is to identify and systematise, on the basis of contemporary empirical research, the psychological mechanisms that mediate the influence of generative artificial intelligence on student well-being, and to substantiate a model of psycho-pedagogical support.

The paper adopts the eudaimonic conception of well-being proposed by C. Ryff, comprising six dimensions: autonomy, environmental mastery, personal growth, positive relations with others, purpose in life and self-acceptance [5]. This choice is not incidental: autonomy and personal growth prove to be the dimensions most vulnerable to the delegation of intellectual work to algorithms. The hedonic tradition, represented by the subjective well-being research of E. Diener and colleagues [6], is drawn upon as a complementary perspective, since satisfaction derived from AI tools may mask the erosion of deeper eudaimonic parameters.

Self-determination theory provides the explanatory frame: well-being is sustained by the satisfaction of three basic needs — autonomy, competence and relatedness [7; 8]. GenAI is capable both of supporting these needs (by lowering the entry barrier to complex tasks and enhancing the experience of competence) and of undermining them (by displacing the student's own authorship and crowding out human interaction). It is precisely this duality that accounts for the non-linear effects observed. The World Health Organization, in designating mental health a global priority, stresses the need for preventive intervention in institutional settings, among which the university is central [9].

Technostress. The transactional model of stress developed by R. Lazarus and S. Folkman explains why the same technology elicits opposite reactions in different students: what proves decisive is whether the situation is cognitively appraised as a threat or as a challenge for which coping resources are available [10]. The operationalisation of techno-stressors proposed by T. Ragu-Nathan and colleagues distinguishes five components — techno-overload, techno-invasion, techno-complexity, techno-insecurity and techno-uncertainty [11]. Subsequent research has confirmed their stable association with emotional exhaustion and reduced satisfaction [12; 13].

The specific character of GenAI-related technostress is revealed in the qualitative study by M. Asad and colleagues: among master's students, techno-insecurity (fear that one's own competences will be devalued) and techno-uncertainty (the impossibility of keeping pace with tool updates) predominate, and the dimensions most affected are autonomy, personal growth and self-acceptance — the very dimensions identified in Ryff's model [14]. N. M. Daud shows that hybrid models of technology adoption intensify technostress responses through the fragmentation of the learning environment [15]. Comparable results have been obtained with foreign-language learners, where technostress responses were associated not so much with language proficiency as with the level of digital competence [16; 17].

Cognitive offloading. The construct of cognitive offloading describes the transfer of cognitive load to external carriers [18]. The classic "Google effect" demonstrated that when external storage is available, people remember not the information itself but the route to it [19]. Generative systems expand this mechanism qualitatively: what is delegated is no longer memory but the operations of analysis, synthesis and evaluation — that is, the core of critical thinking. In M. Gerlich's study (n = 666), a significant negative association was found between the frequency of AI tool use and critical thinking scores, fully mediated by cognitive offloading, with the effect most pronounced among younger respondents [20]. Electroencephalographic data obtained by N. Kosmyna's group indicate reduced neural connectivity during essay writing with a language model compared with unaided work; the authors introduce the metaphor of "cognitive debt" — the deferred price of an immediate saving of effort [21].

Emotional dependence. A four-week randomised controlled trial conducted by the MIT Media Lab in collaboration with OpenAI (n = 981, over 300,000 messages) showed that higher daily intensity of chatbot interaction was associated with increased loneliness, emotional dependence and problematic use, alongside a decline in real-world socialisation [22]. Notably, the advantages of the voice modality, evident at moderate levels of use, disappeared at high intensity. This finding is consistent with the burnout model of C. Maslach and M. Leiter, in which depersonalisation operates as a defensive reaction to resource depletion [23].

The study was carried out as a theoretical-analytical review incorporating elements of structured search. Searches were conducted in Scopus, Web of Science, PubMed and Google Scholar using combinations of descriptors: “generative AI” AND (“well-being” OR “technostress” OR “cognitive offloading” OR “emotional dependence”) AND (“student” OR “higher education”). The search window was 2020–2026; no year restriction was applied to theoretical sources. Inclusion criteria: peer-reviewed publication; presence of empirical data or a systematised theoretical apparatus; focus on psychological variables. Exclusion criteria: purely didactic studies without psychological indicators; preprints without a described procedure (with the exception of two works that attracted wide scholarly attention and are included with an appropriate caveat). The final corpus comprised 32 sources. Methods of processing: content analysis, categorical synthesis and conceptual modelling.

A synthesis of the evidence reviewed supports the claim that the psychological effects of GenAI do not form a single continuum but are distributed across three relatively autonomous loops, each with its own mechanism, symptomatology and targets of intervention (Table 1).

Table 1 — A three-loop model of psychological risk in GenAI-mediated learning

Loop	Psychological mechanism	Indicators	Empirical evidence
Technostress	Imbalance between the demands of the digital environment and coping resources (Lazarus, Folkman)	Techno-overload, techno-invasion, techno-insecurity, emotional exhaustion, fear of competence devaluation	Ragu-Nathan et al. [11]; Salanova et al. [12]; Asad et al. [14]; Daud [15]
Cognitive	Transfer of analysis and evaluation operations to an external system; “cognitive debt”	Declining critical thinking, surface learning strategies, weakened metacognitive control, loss of authorship	Risko, Gilbert [18]; Sparrow et al. [19]; Gerlich [20]; Kosmyna et al. [21]
Affective-relational	Substitution of human support by algorithmic support; parasocial attachment	Loneliness, emotional dependence, problematic use, reduced real-world interaction	Fang et al. [22]; Maslach, Leiter [23]; Jukiewicz [4]

The first conclusion that follows from the table concerns differences in temporal horizon. The technostress loop manifests most rapidly and is the most reversible: reducing the intensity of contact with the technology and raising digital competence attenuate the symptoms within weeks. The cognitive loop is delayed and cumulative — the “debt” accrues imperceptibly and is revealed only in situations demanding independent intellectual effort. The affective-relational loop occupies an intermediate position, yet it is potentially the most persistent, since it affects the structure of the individual’s social ties.

The second conclusion concerns non-linearity. In virtually all the studies reviewed, the relationship between the intensity of GenAI use and well-being indicators is described by an inverted U-shaped curve: moderate use is associated with lower academic anxiety and a heightened sense of competence, whereas intensive use produces the opposite effects [20; 22]. This means that a policy of blanket prohibition is as psychologically ineffective as a policy of unregulated adoption.

The third conclusion concerns the decisive role of mediators. The analysis indicates that the predictor of well-being is not the volume of use as such but the quality of self-regulation. B. Zimmerman’s cyclical model of self-regulated learning (forethought — performance — self-reflection) explains why students with well-developed metacognitive skills use GenAI as an instrument for extending their thinking, whereas students with self-regulation deficits use it as a means of avoiding effort [24]. Academic self-efficacy in A. Bandura’s sense acts as a buffer: the conviction that one is able to handle a task reduces the likelihood of premature delegation [25].

The fourth conclusion concerns AI literacy, which, following D. Ng and colleagues, encompasses understanding, applying, evaluating and the ethical dimension of working with AI [26; 27]. Higher levels of AI literacy are associated with weaker technostress responses and greater digital well-being [16], which makes AI literacy not merely a didactic but also a psycho-preventive category.

The picture obtained allows what may be termed the productivity paradox to be formulated: an instrument that reduces situational strain increases the vulnerability of the person when used over the long term. The mechanism of this paradox is explicable within self-determination theory. GenAI immediately satisfies the need for competence — the task is solved, the text is written, the barrier is overcome. Yet this satisfaction is externally attributed: success is credited to the instrument rather than to the self. Repeated many times over, this produces a structure analogous to learned helplessness with a positive sign: the student retains effectiveness but loses the experience of authorship. This explains why studies simultaneously record rising satisfaction with the process and declining eudaimonic indicators of well-being [4; 6].

A second consideration is cultural. Almost the entire body of empirical data has been obtained in Western and East Asian contexts. Yet the collectivist orientations characteristic of the educational culture of Central Asia may substantially modify these effects. On the one hand, the density of real social ties may act as a protective factor against affective-relational risks. On the other, the high normative significance of academic success and the prevalence of examination anxiety may strengthen the motivation to delegate cognitive work. Empirical verification of these assumptions on samples of Uzbek students constitutes a research task in its own right; an appropriate instrument set would include Ryff's scales of psychological well-being [5], the Perceived Stress Scale [30], the Satisfaction With Life Scale [31] and adapted inventories of technostress responses [11] and academic procrastination [32].

On the basis of the mechanisms identified, a four-module programme is proposed, designed for one semester (32 contact hours) and integrated into the university system of academic tutoring and psychological services (Table 2). The logic of the programme mirrors the three-loop model: each module addresses a particular risk loop, while the fourth secures the institutional consolidation of outcomes.

Table 2 — Structure of the AI-WELL programme

Module	Target loop	Core content	Expected outcome
I. Digital hygiene and regimen	Technostress	Diagnosis of techno-stressors; boundary rules for notifications and study time; recovery techniques; work with fear of competence devaluation	Reduced techno-overload and techno-invasion
II. Cognitive resilience	Cognitive	The "own draft first" protocol: a personal version before consulting AI; critical verification of system output; keeping a log of intellectual authorship	Preserved critical thinking and metacognitive control
III. Real relatedness	Affective-relational	Collaborative learning formats; peer supervision; recognising signs of emotional dependence; access to psychological services	Prevention of loneliness and problematic use
IV. Ethics and institution	All loops	Academic integrity norms; transparent declaration of AI use; staff training; well-being monitoring	A sustainable environment of responsible AI use

Methodologically, the programme rests on the principle of augmenting rather than replacing intellectual effort, formulated in work on the ethics of educational AI [28; 29]. The key methodological device of the second module is the “own draft first” protocol: the student is required to produce a personal version of the solution or text before turning to the generative system, and the subsequent interaction is structured as a critical dialogue with an opponent rather than as the retrieval of a finished product. This sequence preserves the forethought phase of the self-regulation cycle [24] and prevents the accumulation of “cognitive debt” [21].

The paper is theoretical-analytical in character and presents no original empirical data; the structured search did not fully conform to the PRISMA protocol. The rapid turnover of GenAI technologies means that empirical results obtained with the models of 2024–2025 date quickly. The AI-WELL programme requires validation through a quasi-experimental design.

Three principal conclusions may be drawn from the analysis. First, the influence of generative artificial intelligence on students’ psychological well-being cannot be reduced to a single effect; it is distributed across three loops — technostress, cognitive and affective-relational — each with its own dynamics and requiring specific preventive measures. Second, the relationship between the intensity of GenAI use and well-being is non-linear: both excessive use and prohibitive strategies are psychologically unfavourable, while the key mediators are self-regulated learning, AI literacy and academic self-efficacy. Third, the task of the university is not to control access to the technology but to cultivate the cognitive resilience of the individual — the capacity to retain authorship of one’s own thinking under conditions of readily available external intellectual resources.

Further research should involve longitudinal empirical study with samples of students at Uzbek universities, the adaptation of psychodiagnostic instruments to the national educational context, and the validation of the AI-WELL programme within real teaching practice.

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